Wavelet-Based Neural Network Approach to Power Quality Disturbance Recognition

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***Abstract*-- This paper proposes a wavelet-based neural network classifier for recognizing power quality disturbances is implemented and tested under various transient events. The discrete wavelet transform technique is integrated with multiple neural networks using a learning vector quantization network as a powerful classifier. Various transient events are tested, the results show that the classier can detect and classify different power quality disturbance types efficiency.**

***Index Terms*-- Power quality disturbance, wavelet transform, neural network, pattern recognition**

I. Introduction

POWER quality has become an important issue in power systems nowadays. The demand for clean power has been increasing in the past several years. The reason is mainly due to the increased use of microelectronic processors in various types of equipment, such as computer terminals, programmable logic controller, diagnostic systems, etc. Most of these devices are quite susceptible to disturbances of the incoming alternating voltage waveform [1]. Poor power quality (PQ) may cause many problems for affected loads, such as malfunction, instabilities, short lifetime, and so on. Poor power quality is normally caused by power-line disturbances, such as impulses, notches, momentary interruptions, waveshape faults, voltage swell/sag, harmonic distortion, and flicker, resulting in failure of end-use equipment. In order to improve power quality, the sources and causes of such disturbances must be known before appropriate mitigating actions can be taken. A feasible approach to achieve this goal is to incorporate detection capabilities into monitoring equipment so that events of interest will be recognized, captured, and classified automatically. Thus, good performance monitoring equipment must have functions which involve the detection, localization, and classification of transient events.

Wavelet transform (WT) can hence offer a better compromise in terms of localization. The wavelet transform decomposes transients into a series of wavelet components, each of which corresponds to a time domain signal that covers a specific octave frequency band containing more detailed information. Such wavelet components appear to be useful for detecting, localizing, and classifying the sources of transients [2]. Hence, the wavelet transform is feasible and practical for analyzing power quality disturbances.

Santoso *et al*. [3] proposed to extract the features of power quality signals in terms of wavelet coefficients using the multiresolution analysis (MRA) as inputs of the neural network for identifying impulses, voltage sags, and transient oscillations. The detection, localization, and classification processes were performed by visual inspection. It yields low accuracy. Angrisani *et al*. [4] proposed to employ the continuous wavelet transform (CWT) to estimate the disturbance time duration and the discrete wavelet transform (DWT) to estimate the disturbance amplitude. The two features thus obtained are then used to classify the transient disturbance type. It gives medium accuracy.

Santoso *et al.* [5] presented a wavelet-based neural classifier integrating the DWT, and learning vector quantization (LVQ) neural network to become an actual power disturbance classifier. The classifier employed the DWT coefficients as inputs to multiple LVQ neural networks to train and perform waveform recognition but the detection and localization processes were performed by visual inspection. This paper used wavelet-based neural classifier to automatically detect, localize, and classify the transient disturbance type, for high accuracy and low usage time. The underlying approach of the proposed method is to carry out waveform recognition in the wavelet domain using multiple neural networks. A final decision about the disturbance type is made by combining the outcomes of the networks using decision-making schemes.

II. Pattern Recognition For Disturbance Waveforms

Pattern recognition is a process of perceiving a pattern of a given object based on knowledge already possessed. Such recognition tasks are performed in a seemingly effortless fashion by humans or animals, but they are often extremely difficult for computers or any man-made machines. Practical pattern recognition techniques find widespread uses in modern life, such as handwriting recognition, fingerprint identification, and oceanic signal identification to mention a few.

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Power quality disturbance waveform recognition is often troublesome because it involves a broad range of disturbance categories or classes, and therefore, the decision boundaries of disturbance features may overlap. As in most identification and classification work, the ultimate goal is to correctly label the unknown objects (i.e., signals, images, processes) according to their prescribed categories. There are two main approaches to achieve this goal, the parametric and nonparametric approaches [6]. In the pattern recognition framework, the parametric approach, known as the statistical approach, requires a good assumption of the statistical distribution of the pattern data. On the other hand, the nonparametric approach, known as the neural network approach, does not require any statistical assumption of the pattern data. This paper employs the neural network approach for recognizing power quality disturbance waveforms.

III. Wavelet Transform

The method of detection is fairly straightforward. A given disturbance waveform is transformed into the time-scale domain using multiresolution signal decomposition (MSD). Normally, one- or two-scale signal decomposition is adequate to discriminate disturbances from their background because the decomposed signals at lower scales have high time localization. In other words, high scale signal decomposition is not necessary since it gives a poor time localization. Assume that we have chosen a specific type of mother wavelet with L filter coefficients, $h(n)$ and $g(n)$, which form a family of scaling functions $\phi(t)$ and orthonormal wavelet $\psi(t)$, respectively, so that

$$\phi(t)=\sqrt{2}\sum_{n} h(n)\phi(2t-n) \tag{1}$$

$$\psi(t)=\sqrt{2}\sum_{n} g(n)\phi(2t-n). \tag{2}$$

The detection and localization processes are then just a series of convolution and decimation processes at each corresponding scale. At scale one, the electric power signal $c_o(n)$, with N sample points, is decomposed into two other signals, $c_1(n)$ and $d_1(n)$. From the MSD technique, signal $c_1(n)$ and $d_1(n)$ are obtained from

$$c_1(n)=\sum_{k} h(k-2n)\,c_0(k) \tag{3}$$

$$d_1(n)=\sum_{k} g(k-2n)\,c_0(k). \tag{4}$$

As mentioned in several wavelet transform references, signal $c_1(n)$ is a smooth version of the original signal $c_o(n)$, while $d_1(n)$ is the detailed version of the original signal. Both signals are referred to as wavelet transform coefficients (WTCs) at scale one. These coefficients bring the detection information. In power quality disturbance cases, whenever disturbances occur in a given sinusoidal waveform, WTCs are exclusively larger than their surroundings. As will be made clear later, the wavelet transform analysis is sensitive to signals with irregularities. Based on this property, it is clear that wavelet transform analysis is an appropriate tool to detect and localize power quality disturbances. The decomposed signals at scale two are given by

$$c_2(n)=\sum_{k} h(k-2n)\,c_1(k) \tag{5}$$

$$d_2(n)=\sum_{k} g(k-2n)\,c_1(k). \tag{6}$$

The implementation of MSD technique is described by Fig. 1.

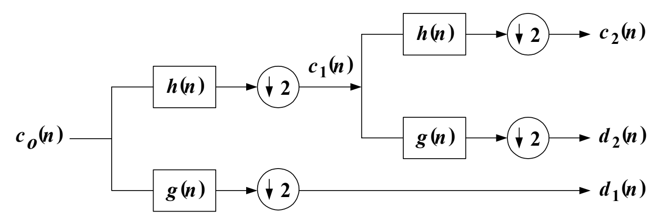

Fig. 1. Multiresolution signal decomposition (MSD) diagram.

Underlying this straightforward process, one should keep in mind that the physical understanding of the detection and localization of equations (3) and (4) is given by

$$c_1(n)=\int_{-\infty}^{\infty} f(t)\phi_{1,n}(t)dt=\frac{1}{\sqrt{2}}\int_{-\infty}^{\infty} f(t)\phi\left(\frac{t}{2}-n\right)dt \tag{7}$$

$$d_1(n)=\int_{-\infty}^{\infty} f(t)\psi_{1,n}(t)dt=\frac{1}{\sqrt{2}}\int_{-\infty}^{\infty} f(t)\psi\left(\frac{t}{2}-n\right)dt, \tag{8}$$

where

$$f(t)=\sum_{n} c_0(n)\phi(t-n)=\sum_{n} c_0(n)\phi_{0,n}(t). \tag{9}$$

The $f(t)$ in (9) can be thought of as "dummy signal" generated by a linear combination of the scaling function at scale zero. Substituting (1) and (2) into (7) and (8), respectively, we have

$$c_1(n)=\int_{-\infty}^{\infty} f(t)\sum_{k} h(k)\phi(t-2n-k)dt \tag{10}$$

$$d_1(n)=\int_{-\infty}^{\infty} f(t)\sum_{k} g(k)\phi(t-2n-k)dt. \tag{11}$$

From (10), it is understood that $c_1(n)$ is simply the smooth version of the original signal $f(t)$, since $h(n)$ has a low pass frequency response. From (11), it is clear that $d_1(n)$ contains only higher frequency components of the signal $f(t)$ because $g(n)$ has a high pass filter response. In practice, the construction of $f(t)$ is not necessary but it is useful in understanding the detection and localization processes as indicated in (7) and (8). However, signals $c_1(n)$ and $d_1(n)$ are actually obtained directly from (3) and (4). This makes the detection and localization processes very straightforward. The detection process for scale two starts from signal $c_1(n)$ where this signal can be thought of as "new" $c_O(n)$. The above process is then repeated. Since the scaling and wavelet functions get wider and wider as the scale increases, time localization is lost. Thus, it suggests that higher-scale decomposition is not necessary. As far as detection in power quality disturbances is concerned, two-scale signal decomposition of the original signal $c_O(n)$ is normally adequate to detect and localize disturbances [1].

The choice of mother wavelet plays a significant role in detecting and localizing various types of disturbances. Daubechies' wavelets with 4, 6, 8, and 10 filter coefficients work well in most disturbance detection cases. At the lowest scale (scale 1), the mother wavelet is most localized in time and oscillates most rapidly within a very short period of time. As the wavelet goes to higher scales, the analyzing wavelets become less localized in time and it oscillate less due to the dilation nature of the wavelet transform analysis. As a result of higher scale signal decomposition, fast and short power quality disturbances will be detected at lower scales, whereas slow and long power quality disturbances will be detected at higher scales. Hence, we can detect both fast and slow power quality disturbances with a signal type. Since Daub4 has the least number of filter coefficients and it gives the shortest support in the family, we use Daub4 in our algorithm.

IV. Learning Vector Quantization (LVQ)

Artificial neural network is a sophisticated networks system that is made of many neurons connected with each other. In this study, the proposed classification is carried out in sets of multiple neural network using a learning vector quantization network (LVQ). The LVQ network is a hybrid network which uses both unsupervised and supervised learning to form classifications [7].

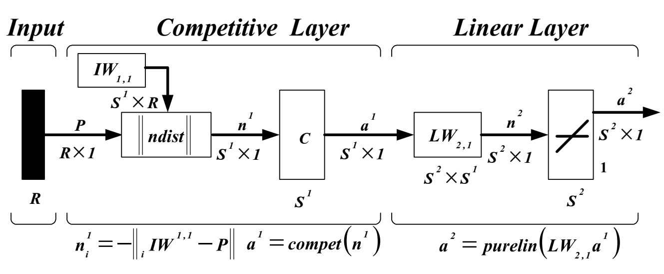

Fig. 2. Learning vector quantization network structure.

In the LVQ network, each neuron in the first layer is assigned to a class and several other neurons are often assigned to the same class. Each class is then assigned to one neuron in the second layer. The number of neurons in the first layer (S^1) will therefore always be at least the number of neurons in the second layer (S^2) and will usually be larger. As with the competitive network, each neuron in the first layer of the LVQ network learns a prototype vector, which allows it to classify a region of the input space. Instead of computing the proximity of the input and weight vectors by using the inner product, the net input of the first layer can be obtained by

$$n_i^1 = -\left\| {}_i w^1 - p \right\|. \tag{12}$$

The output of the first layer of the LVQ network is

$$a^1 = compet\left(n^1\right) \tag{13}$$

Therefore the neuron whose weighting vector is closest to the input vector will output a 1, and the other neurons will output 0. In the LVQ network, the winning neuron indicates a subclass, rather than a class. There may be several different neurons (subclasses) that make up each class. The second layer of the LVQ network is used to combine subclasses into a single class. This is done with the W^2 matrix. The columns of W^2 represent subclasses, and the rows represent classes. W^2 has a single 1 in each column, with the other elements set to zero. The row in which the 1 occurs indicates which class the appropriate subclass belongs to.

$$\left(w_{ki}^2 = 1\right) \Rightarrow \text{Subclass is a part of class.} \tag{14}$$

The LVQ learning rule proceeds as follows. At each iteration, an input vector p is presented to the network, and the distance from p to each prototype vector is computed. Then, the hidden neurons compete. If neuron i^* wins the competition, the i^*th element of a^1 is set to 1. Next, a^1 is multiplied by W^2 to get the final output a^2, which also has only one nonzero element, k^*, indicating that p is being assigned to class k^*. The Kohonen rule is used to improve the hidden layer of the LVQ network in two ways. First, if p is classified correctly, then the weights ${}_{i^*}w^1$ of the winning hidden neuron move toward p. This can be expressed in (15).

$${}_{i^*}w^1(q) = {}_{i^*}w^1(q-1) + \alpha\left(p(q) - {}_{i^*}w^1(q-1)\right). \tag{15}$$

Second, if p was classified incorrectly, then the weights ${}_{i^*}w^1$ move away from p. This can be expressed in (16).

$${}_{i^*}w^1(q) = {}_{i^*}w^1(q-1) - \alpha\left(p(q) - {}_{i^*}w^1(q-1)\right). \tag{16}$$

The result will be that each hidden neuron moves toward vectors that fall into the class for which it forms a subclass and away from vectors that fall into other classes.

V. Wavelet-Based Neural Classification Structure

The basic idea of the wavelet-based neural classifier is to perform waveform recognition in the wavelet domain using multiple neural networks. Fig. 3 shows the schematic block diagram of the wavelet-based neural classifier which consists of preprocessing, processing, and post-processing. The input of the neural network is a preprocessing signal. In this case, the time domain of power quality disturbance waveform is transformed into the wavelet domain before being fed to the neural network. This transformation detects and extracts disturbance features in the form of simultaneous time and frequency information and gradient or slope of the disturbance signal using the dyadic orthonormal wavelet transform. The extracted features help the neural network in distinguishing one disturbance event from another. The processing phase contains a set of multiple artificial neural networks with wavelet transform coefficients as input signals. This processing phase performs waveform recognition in the wavelet domain since all input signals are in the wavelet domain. The output of the processing phase is the type of the disturbances. Since multiple neural networks are utilized, a post–processing phase is required to combine the outcomes of the multiple neural networks in order to make a decision about the disturbance type and to provide a level of confidence for the decision made. The output of the classifier declared that it is a disturbance with belief interval of 85-91% as the degree as of belief.

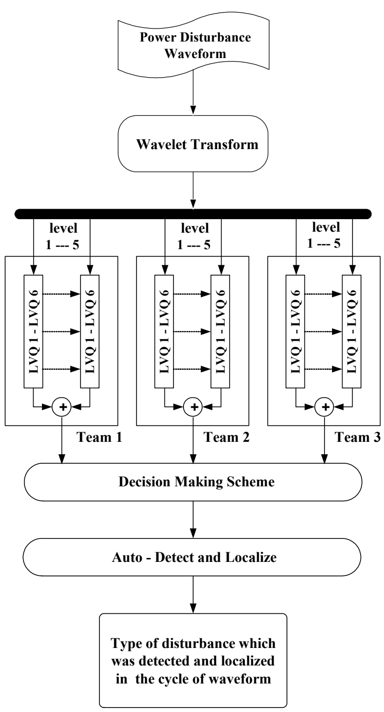

Fig. 3. Schematic block diagram of the wavelet-based neural classifier.

The entire disturbance record (1000 sampling points) is used for this purpose. The disturbance features reside in five scales of decomposed signals. Teams of artificial neural networks which each team consists of 30 learning vector quantization networks are applied. The output of each team is then combined to produce a final decision about the disturbance with one of the decision making schemes. The LVQ must be trained using known disturbance waveforms before they can be used as a part of the classifier. Each of the LVQ is trained separately and their weight vectors are initialized independently. Thus, after training, the weight vectors are different from one another. In the testing phase, these disturbances are tested along with all other prespecified disturbances. The schematic diagram for the testing phase is the same as the one shown in Fig. 3. The use of multiple set of neural networks arises from the need for achieving a higher accuracy rate. This is normally achieved by rejecting ambiguous patterns which cannot be recognized by a neural network. The use of multiple neural networks also provides a means of determining a degree of belief for each identified disturbance waveform. The voting scheme is the simplest method of combining the output of multiple neural networks. A decision is made based on which type of disturbance waveform receives the most votes.

VI. Disturbance Data Set

The wavelet-based neural classifier presented in this work is designed to recognize 6 types of power quality disturbances including of type A low frequency oscillatory transient, type B medium frequency oscillatory transient, type C dc offset, type D sudden sag, type E gradual sag, and type F cyclic voltage fluctuation as described in [8, 9]. Typical disturbance waveforms of these kinds are shown in Fig. 4.

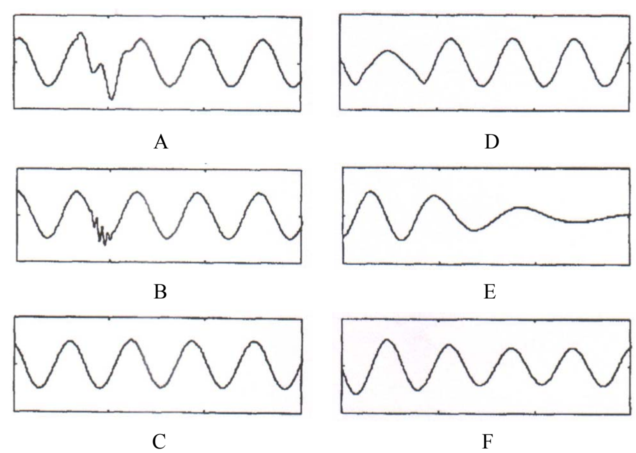

Fig. 4. Typical disturbance categories in this research.

The power quality disturbance data set are split into the training data set and testing data set. Table I shows the number of disturbance records required for each type to train and test the classifier. The total number of disturbance records to train and test the classifier are 780 and 660 records, respectively.

TABLE I
Power Quality Disturbance Data Set

Type	A	B	C	D	E	F	Total
Training	130	130	130	130	130	130	780
Testing	110	110	110	110	110	110	660

VII. RESULTS

This section discusses the simulation of the wavelet-based neural network classifier for recognizing power quality disturbance types. The proposed method is run by using MATLAB program. The random selected signal from 110 signals of each disturbance type is used to test neural networks. The proposed method is able to detect and classify all 6 types for power quality disturbances as shown in Table II. From Table II, All disturbance types tested are differentiated from pure sinusoids. Type E and pure sinusoid are identified with 100 % accuracy. Type A is classified with 92.70 % accuracy and type D is identified with 85.50 % accuracy. These results illustrate that many disturbance types can be recognized easily, and a few, particularly DC offset (type C) and cyclic voltage fluctuation (type F), are difficult to distinguish.

TABLE II
RESULTS OF TESTING CLASSIFICATION METHOD

Type	Correctly	Incorrect	Accuracy rate (%)
Pure Sine	110	-	100.00
A	102	8	92.70
B	98	12	89.10
C	85	25	77.30
D	94	16	85.50
E	110	-	100.00
F	80	30	72.70
Total of accuracy rate = 88.20 %			

After testing all power quality disturbances type A, B, C, D, E, F, and pure sinusoid, the proposed method is able to detect and classify the disturbance types with 88.20 % accuracy. Table III shows the performance of the automatic detection and localization against some of disturbance type. For example, power quality disturbance waveforms of type A (No. 15) have exact position point at 25.60 ms and 25.55 ms for auto-detection and localization on waveform. Thus, the error is 0.20 %. After testing all power quality disturbances type A, B, C, D, E, and F, the performance of auto-detection and localization have the error is less than 5 %.

VIII. CONCLUSION

This paper proposed a prototype of wavelet-based neural network classifier for power quality disturbance recognition and classification. The experimental results showed that the proposed method has the ability of recognizing and classifying different power disturbance types efficiently. This work leads us to believe that wavelet analysis together with neural structure, as a new tool, offers a great potential for diagnosis of electrical power systems in the area of power quality problems.

Although the test result of the proposed power quality disturbance recognition system is quite promising, the real-life power quality disturbance data will not be as simple as those simulated waveforms and the size of sampled waveforms is hard to be sufficiently large. Therefore, further adjustment and modification is required before this proposed power quality disturbance recognition system can be applied in real-life situation.

TABLE III
RESULTS OF AUTO-DETECTION AND LOCALIZATION METHOD

Type	No.	Exact Position (ms)	Auto-Detect and Localize (ms)	Error (%)
A	15	25.60	25.55	0.20
	34	29.20	29.05	0.51
	47	15.60	15.55	0.32
	66	19.20	19.05	0.78
	87	10.40	10.55	1.42
B	15	23.10	23.05	0.22
	34	40.60	40.55	0.12
	47	13.10	13.05	0.38
	66	30.60	30.55	0.16
	87	25.60	25.55	0.24
C	15	23.60	22.60	4.42
	34	20.00	20.10	0.50
	47	27.60	27.60	0.00
	66	24.80	25.10	1.20
	87	30.00	30.10	0.33
D	15	22.40	22.60	0.88
	34	30.00	30.10	0.33
	47	22.40	22.60	0.88
	66	12.40	12.60	1.59
	87	25.20	25.10	0.40
E	15	22.60	22.55	0.22
	34	35.20	35.05	0.43
	47	32.60	32.55	0.15
	66	45.20	45.05	0.33
	87	27.60	27.55	0.18
F	15	22.00	22.05	0.23
	34	29.40	29.55	0.51
	47	24.40	24.55	0.61
	66	12.00	12.05	0.41
	87	19.40	19.55	0.77

IX. ACKNOWLEDGMENT

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XI. BIOGRAPHIES

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